"Global effects of US uncertainty: real and financial shocks on real and financial markets"

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Abstract

We estimate the effects of financial, macroeconomic and policy uncertainty from the United States on the dynamics of credit growth, stock prices, economic activity, bond yields and inflation in five of the main receptors of US foreign direct investment from 1950 to 2019: The United Kingdom, The Netherlands, Ireland, Canada and Switzerland. Our multicounty approach allows us to clearly identify the effects of the different sources of uncertainty by imposing natural contemporaneous exogenity restrictions which cannot be used in a single-country perspective, frequently undertaken by the literature. It also considers international common cycle factors that have been previously identified and which are key to adequately measure the dynamics of the effects of uncertainty shocks on financial and real markets, on a global basis. We use an international FAVAR model to carry out our estimations. This approach permits handling a large data set consisting of variables for more than 45 countries at once. Our results point out to financial uncertainty as the main driver (even more than real uncertainty or the US interest rate) of global economic cycles. We show that increases of US financial uncertainty deteriorate economic activity on a global scale, especially by reducing credit and stock prices, and therefore funding opportunities for firms and households (heterogeneously on a country level basis). Our results emphasize the importance of financial markets, and especially financial uncertainty in the United States, as the main origin of global economic fluctuations, which can be said to describe the recent history of the global economy. They also cast doubts on the ability of uncertainty indicators based on the counting of key words in the media as a barometer of traditional economic uncertainty, known to be theoretically associated to negative outcomes in terms of activity and prices. In this sense, uncertainty indicators based on the estimation and aggregation of forecast errors seem more appropriate, hence producing results in line with the understanding of uncertainty as a negative phenomenon on a macro level, especially for investment prospects.

JEL classification: D80, E44, F21, F44, G15.

Keywords: Macroeconomic uncertainty, Financial uncertainty, Credit markets, Funding, Global business cycles.

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1. Introduction

The effect of uncertainty on economic decision-making has regained interest in the macroeconomics literature. Most researchers and policymakers coincide that the development of the recent Global Financial Crisis (GFC) cannot be fully explained by the combination of traditional market and regulatory failures in the operation and regulation of financial markets. A perverse combination of fundamental uncertainty and externalities in banking seems to have been one major responsible of the crisis.

Fundamental uncertainty, which has been largely ignored in mainstream economics and finance, has an important impact on economic agents' everyday decision-making. While most psychologists and behavioral economists take the rational agent model of equilibrium-based economic theory as their point of departure, hard to rationalize decisions made by banks and global investors before and during financial crises have motivated a renewed interest in studying whether Keynesian "animal spirits" are important drivers of financial and business cycles. In fact, this term was recently drawn to wide attention in economics by the publication in 2009 of Akerlof and Shiller's book of that title. The book studies economic agents' behavior in the context of the new behavioral economics (Sent, 2004), which uses neuroscience to help economists understand the behavior of agents in real-world experimental situations. The main concern is to understand and predict behaviors which seem to challenge the predictions of theoretical models relying on rationality axioms of individual behavior.

The interest in revisiting the effects of real uncertainty on financial and macroeconomic outcomes is clear (see, for instance, Stokey, 2008; Bloom, 2009; Jurado et al., 2015; Baker et al., 2016; Bordo et al., 2016; Ludvigson et al., 2020). However, there is still a heated debate on the main sources of uncertainty (macroeconomic, financial, or policy), the best way of measuring it (ex-ante vs. realized measures), and its main propagation mechanism. Regarding this last point, the role of systematic uncertainty on firms' sources of financing and its relationship with investment and real economic activity has not been deeply explored.

In traditional macroeconomic models, the real and monetary sides of the economy are independent from one another. Money is neutral, in the sense that investment, growth and cycles can be studied without referring to money, credit and the banking system. These features are added at a later stage to provide the appearance of a more realistic economic model. However, they are not central to the discussion of why some countries grow faster than others, or why investment and employment rapidly decay during periods of high aggregate uncertainty.

The great recession triggered by the GFC of 2008-2010 renewed interest in studying the interdependence between real and financial variables, and especially the central role played by banks and banking credit in plumbing real economic outcomes. Today there is little doubt that firms require credit to finance their investment plans and that, in the absence of perfect capital markets, internal and external capital are not perfect substitutes (Fazzari et al., 1988; Bottero et al., 2020; Cao and Leung, 2020). The idea that investment depends on financial factors, such as access to new debt or equity financing, is gaining increasing acceptance among macroeconomists.

In this context, some "old" Keynesian ideas on money and credit markets are resurging. Important attempts of integrating credit into the discussion of production through a careful sequential analysis of economic events are developing in the profession. Output, production, unemployment, and other important real variables cannot be fully understood without first understanding the role of the banking system, money debt contracts and credit.

Uncertainty plays a key role on the dynamics of credit and, therefore, on the dynamics of economic activity in general. During booms, as banks are optimistic about the ability of firms to repay their debt, they tend to lower their creditworthiness standards and extend more loans. The underlying credit boom leads to more investment, higher growth, and more lending. The opposite happens during economic downturns. Pessimism about the future capacity of firms to validate their loans takes banks to curtail firms' credit. In fact, credit crunches occur during periods of extreme pessimism on future economic performance (Wisniewski and Lambe, 2013; Mehrotra and Sergeyev, 2020). Constraints for lending are generally not created by deposit shortages, but by the unwillingness of banks to lend in moments of high uncertainty.

Uncertainty is not equivalent to risk. In the real world, the production of goods takes time. The payoff associated with an action is separated from the moment of choice by some period of calendar time (Davidson, 1991; Brandolini et al., 2011; Istiak and Serletis, 2020). In the real world, true uncertainty is not captured by the objective or subjective probabilities with which individuals make decisions on risky alternatives. In a true uncertainty environment, even when objective relative frequencies have existed in the past or subjective probabilities exist today, the decision maker believes that during the calendar time elapsed between the moment of deciding and the payoff, unforeseeable changes may occur. The past is unchangeable and future results are incalculable through a probabilistic approach. In this type of environment, the availability of funding sources and "animal spirits" are the driving forces of investment, and banking credit is the key link between investment projects and the beginning of production processes.

This paper studies the relation between uncertainty and real economic activity by exploring the link between uncertainty and the availability of firm financing through bank credit and capital markets. Its contributions to the literature are four. First, we contribute to the ongoing debate on which type of uncertainty matters most by including measures of real, financial, and policy uncertainty, and comparing their effects on credit, stock markets, GDP, and other macroeconomic variables in ten developed countries, including five of the main receptors of US foreign investment.[1] Following a FAVAR approach, and using recently developed measures of uncertainty for the United States (Jurado et al., 2015; Ludvigson et al., 2020), we show that financial uncertainty is the main source of financial and macroeconomic fluctuations in these countries. Second, unlike most papers in this strand of the literature, we do not just study the real effect of uncertainty on the economy, but additionally we study its transmission channels. Specifically, we study the financial channels (credit, stock market) through which uncertainty shocks propagate to the macroeconomy. Third, by focusing on many developed countries, we capture the global nature of uncertainty that must be included in economic modeling for identification purposes. We use the different uncertainty measures built for the United States economy and consider their effect on other developed economies' financial and macroeconomic variables. Uncertainty measures are, therefore, exogenous to the other variables included in the FAVAR analysis. Finally, our results highlight the importance of taking fundamental uncertainty seriously: It is the unexpected, unpredictable component of (mostly financial) uncertainty measures that matter.

The remainder of the paper is the following. The second section presents a literature review. The third is a methodological section. The fourth section briefly describes the data used in the empirical analysis. The fifth presents our main results, and the last section concludes.

[1] These ten countries are the only developed countries for which sufficiently long time series on macroeconomic variables are available.

2. Literature Review

a) Measuring the effects of uncertainty shocks

Recently, the macroeconomics literature has pooled substantial evidence documenting a negative relationship between economic activity and macroeconomic uncertainty (see for instance Bloom, 2009; Bloom, 2014; Jurado et al., 2015; Segal et al., 2015; Baker et al., 2016; Nakamura et al., 2017; Meinen and Roehe, 2017; Bloom et al., 2018; Berger et al., 2020). There is now little doubt that uncertainty raises sharply during recessions, and is associated with a decreasing in labor, and especially in investment. We also know that uncertainty is negatively related to stock prices (e.g., Bansal and Yaron, 2004; Bekaert et al., 2009; Arouri et al., 2016; Liu et al., 2017), and with credit growth (e.g., Gissler et al., 2016; Bordo et al., 2016; Hu and Gong, 2019). However, modeling the causal effects of uncertainty on macroeconomic variables is a challenging task. There are basically three reasons for this: First, until very recently there were not accurate proxies for macroeconomic or financial uncertainty in the literature. Second, there is an inherent difficulty in setting down what comes first, the increment in uncertainty or the fall in economic activity. Third, uncertainty, credit, output, and prices are driven by global factors, and the joint modeling of these phenomena requires going beyond the traditional focus on individual countries that characterized the macro-uncertainty literature. Here we describe how we tackle these three issues in relation to the previous literature.

Regarding the first point, uncertainty proxies frequently used in the macro-literature do not seem to conform to our intuition about the phenomenon, but instead they allegedly can be said to confound different concepts (see Scotti, 2016; Jurado et al., 2015). For instance, volatility measures (of the market, or of real activity) blend uncertainty with other notions such as risk or risk-aversion. They also fail to distinguish what part of such volatility is expected, and what is unforeseeable, hence, they are unable to differentiate expected uncertainty from its realization, which in turn, has important consequences for the quantification of the effects of uncertainty on the real economy (Berger et al., 2020) and on asset prices (Dew-Becker et al., 2019). On the other hand, proxies of uncertainty that rely on survey of professional forecasters, available only for a very reduced number of series, might fail to capture the conditional expectations of the economy as a whole and instead could be more of an expression of different opinions than of uncertainty (Diether et al., 2002). And, even if forecasts are unbiased, the disagreement in analysts' point forecasts is not generally equivalent to forecast uncertainty (Lahiri and Sheng, 2010) and it may confound the notion of fundamental uncertainty (or ambiguity in some contexts) with the notion of risk (Rossi et al., 2019). Aiming to overcome the criticisms, two branches of the empirical literature have emerged following the works by Baker et al. (2016) and Jurado et al. (2015). The first line uses uncertainty-related counts of key words in the media to construct uncertainty indicators that gauge policy uncertainty in the environment in a comprehensive fashion without resorting to the estimation of volatilities or surveys' information. The second set of studies, while still relies on the estimation of volatilities, aims to isolate from the data the unexpected variation of the series under study, using the information conveyed by hundreds of macroeconomic indicators and financial variables. In this way, it aims to separate unexpected from expected variation (See Bloom, 2014; Datta et al., 2017; and Nowzohour and Stracca, 2020 for recent surveys of this literature). Here we employ macroeconomic, financial, and real uncertainty indicators proposed by Jurado et al. (2015) and Ludvignson et al. (2020), and the Economic Policy Uncertainty (EPU) and Equity Market Uncertainty (EMU) Indices by Baker et al. (2016) joint to other indices alike.

The second point, which is more subtle, but that makes even more challenging to isolate the causal effects of uncertainty on financial and real markets is that, being uncertainty a second moment variable and real activity (and asset prices) first moment variables, there is no compelling reason to set uncertainty ahead or after such variables in a traditional recursive VAR system in order to achieve identification (as done in Jurado et al., 2015; or Baker et al., 2016), or to set equivalent zero restrictions in the B matrix of the SVAR system (as done for instance in Angeline et al., 2018). Moreover, policy uncertainty, which is itself a source of macroeconomic (and financial) uncertainty, can respond to current and anticipated future economic conditions, challenging again the recursive identification strategy. Indeed, contractions of the real economy seems to agree with the presence of compound shocks in the markets that involve negative first moment shocks and positive second moment shocks that might occur simultaneously (Bloom et al., 2018). Facing this panorama, the empirical literature has explored other forms of identification, like imposing a parametric shape on the time-varying variance of the shocks within the system (Carriero et al., 2018) or resorting to external events and variables to achieve identification (Ludvigson et al., 2020), inspired by moment inequality constraints pioneered by Andrews and Soares (2010).

All the literature above aims to identify the effects of uncertainty shocks within a domestic economy (e.g., United States). Hence, it faces the challenges just described, which are far from being solved, because they are intimately related to the traditional difficulties of identification of monetary and fiscal policy shocks in macroeconomics, recently summarized by Nakamura and Steinsson (2018). This brings us to the third problem for estimating causal effects of uncertainty on markets. In this respect, we totally depart from the aforementioned literature, as we focus on the international propagation of uncertainty shocks from the US to the global real and financial markets. This fact allows us to overcome the aforesaid criticisms, as we can set our identification scheme based on the imposition of zeros in the B matrix of our SVAR system, in a natural and defendable way. Indeed, our identification strategy mainly relies on the largely documented fact that the US economy is a source of shocks to the rest of the world, and it rarely behaves as a receiver of shocks (of uncertainty or of any other kind), at least contemporaneously, which is enough for identification in our framework.

Recent literature has explored the international dimension of uncertainty shocks by extracting common factors that are used as proxies to characterize macroeconomic or financial uncertainty. For instance, Mumtaz & Theodoridis (2017), decomposing the time-varying variance of macroeconomic and financial variables into contributions from country-specific uncertainty and common uncertainty, find that the common component of uncertainty plays an important role in the variability of nominal and financial variables across countries. In line with this, Bonciani & Ricci (2020) study the impact of sudden increases in global financial uncertainty on advanced and emerging economies. The authors show that financial uncertainty shocks generate adverse consequences on countries' output, trade, and unemployment. In addition, the effects of uncertainty are more severe in countries with a higher degree of trade or financial openness, or those countries with institutional weaknesses. On the other hand, Carriero, Clarck & Marcelino (2020) find that, for a set of industrialized economies, international macroeconomic uncertainty produces a reduction in output and stock prices, and it also generates adverse effects on the labor market. Additionally, Cuaresma, Huber & Onorante (2020) report that global uncertainty has a negative effect on output, price levels, exports, interest rates and equity prices in G7 countries. Furthermore, the authors also find that when countries have fragile economic systems the effects of global uncertainty have a greater impact on their economic fundamentals. Cesa-Bianchi et al. (2020) emphasize on the importance of considering the international dimension of uncertainty shocks. They specify a multi-country factor-augmented panel VAR for analyzing the effects of stock market volatility (as a proxy for uncertainty) on economic growth. This is the closest study in the literature to ours. The authors find that global common factors, underlying stock market volatilities of countries around the world, seem to be responsible for most of the negative relationship between output growth and stock market volatility, and that single-country approaches to the problem could yield empirically biased estimates due to the omission of such cross-national common factors. Nonetheless, we take distance from the aforementioned literature in several important ways that we list in what follows, which at the same time bring us closer to the literature on world business cycles, both real and financial (see for instance Lumsdaine and Prasad, 2003; Kose et al., 2003ab, 2008; Jorda et al., 2019; Ha et al., 2019; Auer et al., 2017; or Monnet and Puy, 2020). Indeed, the proximity of our work with the literature on global business cycles allows us to propose uncertainty in the US as a main driver of the world financial and real cycles in line with claims by Rey (2013) who highlights how the fluctuations in VIX tend to drive global financial cycles, influencing global asset prices and financial flows (see also Miranda-Agrippino and Rey, 2015b; Miranda-Agrippino and Rey , 2020; Iacoviello and Navarro, 2019).

Our research complements and contributes findings by Cesa-Bianchi et al. (2020). First, we are interested in a different, although related, phenomenon: while they access the effects of common-volatility factors on individual country growth, we are interested in the uncertainty spillovers from the US to the rest of the world. For this reason, they assume that non-country dominates over the others, while we assume the opposite. This is an important difference, considering the recent literature on global credit and real cycles, which directly emphasizes the dominant role of the US economy and in particular its monetary policy, which seems to act as a source of cycles' commonality between the world's economies (see Miranda-Agripino and Rey, 2005; Ammer et al., 2016; Jorda et al., 2019). Second, Cesa-Bianchi and coauthors only consider output growth and log-volatility in their model. They do not include interest rates, prices, or credit markets, neither at the global or the local level. Our G-FAVAR models seek to capture the whole dynamics of the real and financial sides of the economy, and our comprehensive setting is designed to reduce the bias in our estimates due to omitted variables, which, as emphasized by the already mentioned literature on world cycles, and the literature on the determinants of credit dynamics, must not be ignored (see for instance Bordo et al., 2016). Third, we consider various dimensions of financial, real, and economic policy uncertainty, which consider recent advances in the measurement of uncertainty. Finally, our methodological approach (and the recently assembled data set by Monet and Puy, 2020) allows us to explore the impacts of uncertainty shocks on an individual country basis. This is important, because we can identify similitudes and important differences across countries regarding the propagation of uncertainty to real economies and financial markets.

Regarding some recent papers have studied the spillover effects of uncertainty from the US to the rest of the world. Belke & Osowski (2019) study the international effects of political uncertainty from the Eurozone and the USA in 18 OECD countries. In this paper, the authors find that an increase in economic policy uncertainty has a strong negative impact on economic activity, consumer prices, stock prices and interest rates. Additionally, they find that political uncertainty shocks originating in the US have a greater impact than those originating in the Euro Zone. The authors also find a high degree of synchronization between the responses of national variables to a foreign uncertainty shock, indicating evidence of an international business cycle. Also, Rivolta & Trecroci (2020) study the transmission of financial and macroeconomic uncertainty from the US to a set of emerging market economies (EMEs). The authors show evidence that adverse shocks to aggregate US uncertainty are associated with sharp contractions in some EMEs' business cycles. However, they find significant cross-country heterogeneity. In addition, they also detect widespread declines in stock market values, which support the so-called Global Financial Cycle hypothesis. Finally, Bhattarai et al. (2020) study global spillovers from US uncertainty to international real and financial markets. They find evidence in favor of flight to safety/quality channel in the propagation of uncertainty shocks, according to which investors seem to pull capital out of emerging markets in the face of increasing US uncertainty, country that is perceived as a safe heaven. The international process of portfolio rebalancing ends up increasing the costs of borrowing for emerging economies, decreasing their capital inflows and asset prices. None of these studies emphasize on the role of credit markets on the propagation of uncertainty, nor they assign a separate (but complementary) role for financial and real uncertainty, which is crucial for our approach. In addition Bhattarai and coauthors only consider emerging markets in their study, and their model lacks controls for the world-factors that drive financial and real cycles. Lastly, their approach, which makes use of a random coefficients panel VAR, forces them to pool their estimations into two groups of countries to obtain cross-sectional average effects, keeping them from analyzing uncertainty spillovers on an individual country basis.

b) Theoretical background and mechanisms of uncertainty transmission: the role of financial markets

The main modern conceptual framework in economics for understanding the effects of uncertainty on the decisions of firms regarding labor and investment was born within the paradigm of irreversible investment. According to this literature, future investment opportunities can be treated as real options, and therefore in the face of uncertainty it might be optimal to implement a "wait and see" strategy until uncertainty is resolved, rather than undertake costly investment with uncertain consequences. Such micro-considerations remain in the aggregate and, indeed, can lead to uncertainty-driven business cycles (Bernanke, 1983; Bertola and Caballero, 1994; Abel and Eberly, 1996; Leahy and Whited, 1996; Caballero and Pindyck, 1996; Bloom et al., 2007; Bachmann and Bayer, 2013; Bachmann et al., 2013; Bloom, 2009; Bloom et al., 2018), which can be amplified (or justified) by traditional sticky-price-like frictions (Fernández-Villaverde et al., 2011; Basu and Bundick, 2017). Analogous channels have been proposed to understand the effects of uncertainty on consumption, especially of durable goods (Eberly, 1994) that have been empirically documented as well (Romer, 1990) and, which complement the literature that emphasizes the precautionary saving channel that might lead from higher uncertainty to lower consumption (Bansal and Yaron, 2004).

An active branch of the recent literature has emphasized on the role of financial markets for the transmission of uncertainty shocks (e.g., Gilchrist et al., 2014; Bollerslev, 2009; Popp and Zhang, 2016; Caldara et al., 2016; Bonciani and Roye, 2016; Alfaro et al., 2018; Cesa-Bianchi and Fernández-Corugedo, 2018; Alessandri and Mumtaz, 2019; Alessandri and Bottero, 2020); Gächter et al. 2020). All in all, it might be the case that even if a firm is willing to invest (i.e., its option value for waiting is too low or the cost of waiting is extraordinary high) they still may be unable to do so, should them be unable to rise funds in the markets for capital (credit or equity). Indeed, there is evidence in the literature that a raise in uncertainty reduces credit creation and the ability of firms to accessing fresh credit lines (Gissler et al., 2016; Bordo et al., 2016; Hu and Gong, 2019), which might be a consequence of a self-insurance mechanism that induces banks to accumulate capital when uncertainty raises, and in the process, to reduce the supply of credit (Valencia, 2017) or a consequence of the stickiness in bank loan rates (Bonciani and Roye, 2016).

The literature has also expanded the credit-channel of uncertainty to an international level (see Choi, 2018; Choi et al., 2018; Gete and Lelkadse, 2018). In general lines, international creditors may react to an increase in uncertainty in their original economies by reducing their exposition to foreign markets, to satisfy risk-taking constraints on their international portfolio holdings. It could also be the case that if a peak of uncertainty in the US is interpreted as signal of future higher domestic uncertainty in other countries, as seems to be the case given the high cross-sectional correlation of uncertainty proxies around the world (Nowzohour and Stracca, 2020), such an increase may lead to higher precautionary savings which do not remain in the domestic economies but that flow abroad, reducing domestic demand. For this reason Fernández-Villaverde et al. (2011) claim that rising uncertainty can be dangerous for growth in small open economies, in line with the results of Julio and Yook (2016) who document results consistent with the view that political uncertainty deters foreign investment.

3. Methodology

In our baseline scenario we identify the effects of real and financial uncertainty emerging from the Unites States on credit, economic activity, asset prices, and other macroeconomic variables, in five of the most financially interconnected countries with the US. To this end, we employ a multi country FAVAR model. In our empirical results we estimate a VAR for each country separately, but all models are linked by international factors, which describe the cross-country dynamics of the business and financial cycles around the world and consider the existence of cross-sectional shocks to the dynamics of credit, activity, prices, interest rates, etc. The cross-national nature of our data set allows us to impose erogeneity restrictions in the time of the effect of uncertainty on the domestic variables. Indeed, US uncertainty shocks are assumed as contemporaneously exogenous from the perspective of individual countries. We conduct extensive robustness exercises, changing the countries that are shock receptors, we identify the effects of an uncertainty shock on the US economy itself, by resorting to sign restrictions mainly to verify that the shocks are able to reproduce the induced dynamics of uncertainty from a single country perspective previously documented by the literature, and we also include several additional variables like the US interest rate in our data set, as to increase the scope of our controls. In all the cases the documented effects on the macro variables, and particularly relevant on credit, remain virtually unchanged.

a). Factor augmented vector autoregression

Bernanke et al. (2005) proposed FAVAR models, seeking to overcome two important drawbacks of the original VAR framework; namely, traditional VARs force us to exclude too many variables from the estimation because otherwise it becomes feasible to achieve first-order efficient estimations, and it might even be the case that estimation itself becomes unfeasible. This is a consequence of the high number of coefficients associated with each variable in a VAR representation. Therefore, the model can handle only a relatively low maximum number of shocks, given by the number of variables that make the estimations possible. This strategy leaves unexplained different dynamics outside the system, which in the case of multicounty exercises, as the one that we undertake here, are fundamental from the perspective of the researcher and the policy maker. In the same vein, traditional VARs usually lack many controls on the confounding dynamics associated with the included variables, which may derive in estimation biases on the subset of the dynamics that is successfully represented. Second, the FAVAR model allows constructing direct estimations of abstract concepts such as 'global economy activity', 'global interest rates' or a 'global price push', and alike, without having to resort to other proxys that in the best case may be inaccurate or difficult to justify, and which are of paramount importance when working from a multicounty perspective.

Let's consider a traditional VAR representation of an individual country given in reduced form by:

$$\mathbf{Y_t} = \mathrm{A(L)}\mathbf{Y_{t-1}} + \mathbf{e}_\mathrm{t}, \tag{1}$$

where $\mathbf{Y_t}$ is a $(M \times 1)$ vector containing the M variables of the model for each country, $\boldsymbol{A(L)}$ is polynomial in the lag operator of order *d*, $\mathbf{e}_\mathrm{t}$ is a vector of a given country's residuals . The series included in $\mathbf{Y_t}$ are credit, economic activity, stock prices, inflation and the country bonds' yield. One representation as the former is used for each country in our data set, which is enriched by a common factor structure that describes the multicounty shocks to the same variables across time and countries.

Thus, $\boldsymbol{Y_t}$ can be seen as a vector of observable variables that captures the system dynamics in a given domestic economy at any time, to which we have to add $\boldsymbol{F_t}$, a $K \times 1$ vector of 'factors' that contains unobservable shocks which determine the joint dynamics of the global economy, which are not included in $\boldsymbol{Y_t}$. The multivariate dynamics of $(\boldsymbol{Y_t}, \boldsymbol{F_t})$ is described by:

$$\begin{bmatrix} \boldsymbol{F_t} \\ \boldsymbol{Y_t} \end{bmatrix} = \boldsymbol{A(L)} \begin{bmatrix} \boldsymbol{F_{t-1}} \\ \boldsymbol{Y_{t-1}} \end{bmatrix} + \boldsymbol{V_t}, \tag{2}$$

where $\boldsymbol{V_t}$ is a vector of errors with zero-mean and variance-covariance matrix $\boldsymbol{Q}$. Equation 2 is a FAVAR model. This system cannot be directly estimated as a consequence of the factors $\boldsymbol{F_t}$, which are non-observable. Hence, such factors must be also estimated in the process, using techniques such as principal components, singular value decomposition or the Kalman filter. Herein, the total number of informational series included in the factor estimations, $\boldsymbol{X_t}$, are N, and this set accounts for all available variables for all countries in the original data set, not only for those countries analysed, as described in the data section, so that we guarantee that $K + M \ll N$. We follow the strategy proposed by Bernanke et al. (2005), which consists of two steps: in the former step, we estimate the common components of the global system, $\boldsymbol{C_t}$, using the first K principal components of $\boldsymbol{X_t}$. The cardinality of K is determined using the criterion proposed by Bai and Ng (2007) to estimate the number of dynamic or primitive factors in a large data set. Then, in a second step, we either directly add such factors to the individual country system, $\boldsymbol{\widehat{F}_t} = \boldsymbol{\widehat{C}_t}$ (non-orthogonalized factors) or we extract from $\boldsymbol{C_t}$ the variation explained by the observable factors contained in $\boldsymbol{Y_t}$. This is possible simply by taking the residuals of a linear projection of $\boldsymbol{C_t}$ onto $\boldsymbol{Y_t}$, and labelling these residuals as the estimated orthogonalized) factors $\boldsymbol{\widehat{F}_t}$.

Replacing $\boldsymbol{F_t}$ by $\boldsymbol{\widehat{F}_t}$ in equation 2, enables us to estimate the terms in equation 2 by ordinary least square regressions. It is also possible to construct impulse response functions (IRF) in this case, using the MA representation of the system in equation 2. The MA representation exists under suitable stationary conditions as in any VAR model[2].

b). Identification of structural shocks

The reduced form VAR in equation 2 can be rewritten in terms of white noise innovations, $\boldsymbol{V_t}$, as follows:

2 Such standard conditions can be found, for instance, in Lütkepohl (2006).

$$\begin{bmatrix} \widehat{\boldsymbol{F}}_t \\ \boldsymbol{Y}_t \end{bmatrix} = \begin{bmatrix} \overline{\boldsymbol{F}}_t \\ \overline{\boldsymbol{Y}_t} \end{bmatrix} + \boldsymbol{C}(\boldsymbol{L})\boldsymbol{V}_t, \tag{3}$$

where $\overline{\boldsymbol{F}}_t$ and $\overline{\boldsymbol{Y}_t}$ are the unconditional means of the processes, and $\boldsymbol{C}(\boldsymbol{L})$ is a polynomial in the lag operator of infinite lag order. Structural innovations can be recovered from the system in equation 3, imposing theoretical restrictions on the VAR representation. In other words, multiplying the matrices in $\boldsymbol{C}(\boldsymbol{L})$ by a matrix $\widetilde{\boldsymbol{B}}$, which contains as many theoretical restrictions as needed to just-identify the system (or to achieve partial identification, depending on the interests of the researcher). In this case, we have that $\widetilde{\boldsymbol{B}}^{-1}\boldsymbol{V}_t = \boldsymbol{\varepsilon}_t$, and therefore, $\boldsymbol{C}(\boldsymbol{L})\widetilde{\boldsymbol{B}} = \boldsymbol{\Phi}(\boldsymbol{L})$, where $\boldsymbol{\varepsilon}_t$ is a vector of dimensions $(M+K)\times 1$, which contains the structural innovations, and $\boldsymbol{\Phi}(\boldsymbol{L})$ are the structural IRFs of the system, as stated in equation 4:

$$\begin{bmatrix} \widehat{\boldsymbol{F}}_t \\ \boldsymbol{Y}_t \end{bmatrix} = \begin{bmatrix} \overline{\boldsymbol{F}}_t \\ \overline{\boldsymbol{Y}_t} \end{bmatrix} + \boldsymbol{\Phi}(\boldsymbol{L})\boldsymbol{\varepsilon}_t\,. \tag{4}$$

One approach proposed by Sims (1980) to perform the whole system identification is to assume $\widetilde{\boldsymbol{B}}$ as one of the triangular matrices that derive from the Cholesky factorization of the variance-covariance matrix in the reduced form model, $\boldsymbol{Q}$. This approach is indeed natural in our case, in which due to the multicounty nature of our estimations we can assume that both the international factors and the uncertainty indicators are contemporaneously exogenous to the rest of the system (in particular to the domestic economy variables). To achieve a just-identify system it is enough to impose some additional fast-slow moving variable restrictions, according to which the GDP in each country takes more than a period to react to the other domestic economy variables, and credit does not react contemporaneously to prices of good or assets.

4. Data

We carried out our estimations in the baseline scenario for five developed countries, which are major recipients of US foreign direct investment during the sample period: The United Kingdom, The Netherlands, Ireland, Canada, and Switzerland. We use quarterly data from December 1963 to December 2019, the largest time span available for credit data in this set of countries[3]. To capture the dynamics of credit growth, stock prices, economy activity, long-term bond yields and inflation, we use the database assembled by Monnet and Puy (2020) at the International Monetary Fund, who gather cross-country quarterly data of these economic aggregates from 1950 to 2019. We use uncertainty indices estimated as conditional volatilities of the unpredictable component of a set offinancial and macroeconomic variables, as provided by in by Jurado et al. (2015) and Ludvigson et al (2020) on one of the authors' web page: www.sidneyludvison.com.

We consider two different types of uncertainty, financial and real. We also use word count uncertainty measures using the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016) and the Financial Stress Indicator developed by Püttmann (2018) for the United States, both publicly available at www.policyuncertainty.com. Additionally, given the importance of considering the international dimension of uncertainty shocks (Cesa-Bianchi et al. 2020), we include two global factors calculated using all available series for 45 countries in each period at the global level. This allows us to capture the dynamics of financial and business cycles at the global level while controlling for cross-sectional shocks. Finally, we also include the US Fed Funds interest rate in some additional estimation, retrieved from the web page of the Federal Reserve of St, Louis (Fred)

5. Results

In this study we use a FAVAR model to study the effect of (financial, macroeconomic, and policy) uncertainty on aggregate real and financial variables for a set of five developed economies with high US foreign direct investment, the UK, Netherlands, Switzerland, Canada, and Ireland. Most papers in the literature study the effect of uncertainty on real or financial variables in the context of a single country, mainly the US. Uncertainty measures are built using variables that are closely related to those on which the effect of uncertainty is observed, lifting doubt on the exogeneity of these measures. In our case, we built use uncertainty measures built using US macroeconomic, financial, and policy data and evaluate their effect on other countries for which these measures are truly exogenous. The FAVAR approach enables us to estimate country-specific responses to uncertainty shocks in a feasible specification and to

[3] In addition, the baseline specification of the FAVAR model was also estimated using five different developed countries (Germany, Italy, Sweden, Japan, and Australia), in which US direct investment is not as important as in the first set of countries, to test whether the main results presented were specific to the initial set of countries or can be extended to developed countries more generally, which seem to be the case.

overcome the curse of dimensionality. We estimate different specifications of our model, some of which include only one type of uncertainty shock and others in which various types of uncertainty shocks are simultaneously included. Additionally, unlike most related studies, we include both macroeconomic and financial variables in our FAVAR analysis. Hence, we can identify which type of uncertainty matters more and through which channels they propagate to the economy, allowing for country-heterogeneous responses.

We present results for six different specifications of the model. In all of them, five country-specific variables are included: Credit growth, real growth, stock market returns, first difference of the interest rate, and prices growth. The baseline model (first specification) includes two orthogonal global factors, together with financial and real uncertainty of the US. The second specification of the model includes two non-orthogonal global factors, alongside with financial and real uncertainty of the US. The third specification includes two orthogonal global factors, a financial stress indicator and the economic policy uncertainty indicator of the US. The fourth includes one orthogonal global factor, the federal funds (shadow) rate, and the real and financial uncertainty indexes of the US. The fifth corresponds to the baseline model, but in which the identification was achieved using sign restrictions where the stock markets and credit markets were assumed to decrease for one period after an uncertainty shock in financial or real uncertainty. Finally, the last specification corresponds to the baseline model estimated with five different developed countries in which US foreign direct investment is minor, namely Germany, Italy, Sweden, Japan, and Australia.

a) Baseline model

Figures 1 through 5 present impulse response functions for the baseline model. Figure 1 presents the response of credit to a shock in financial (top panel, blue) and real (bottom panel, red) uncertainty. When a financial uncertainty shock occurs, the initial response is a credit contraction in each of the five countries. This negative response of credit markets is stronger a longer for Canada and Ireland, in which mean reversion happens only four quarters later. In the other three countries a return to the steady state occurs within two quarters. Notably, the response of credit to a real uncertainty shock is milder. In two countries there is no statistically significant response (Switzerland and Ireland), while in the other three the response is negative but exhibits a rapid reversion. These results show that credit markets are mostly affected by financial uncertainty shocks. The effect is negative, indicating that credit contracts when uncertainty in financial markets increases. Results do not allow, however, to disentangle the extent to which supply, and demand factors contribute to the overall credit reduction. Macroeconomic uncertainty, on the contrary, does not considerable affect credit dynamics in most countries.

Figure 1. Credit Response to Uncertainty Shocks (Baseline Model).

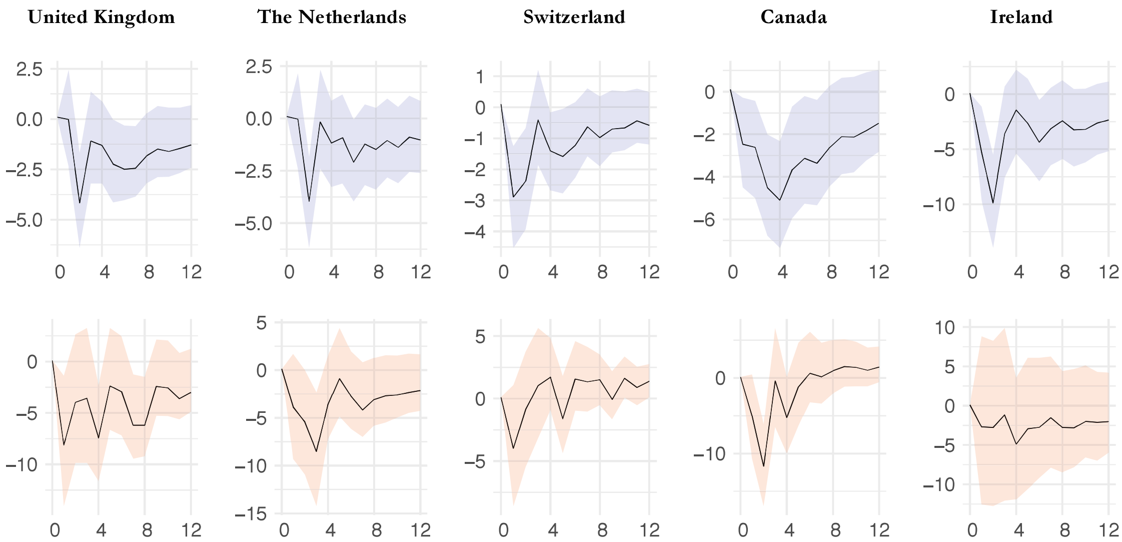

Fig 1. Credit Response to Uncertainty Shocks in the baseline model. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Similarly, the response of GDP is larger when financial uncertainty shocks occur, as shown in Figure 2. Three countries, the UK, Switzerland, and Canada experience real output contractions of about four quarters when financial uncertainty shocks happen. GDP is also negatively affected by these shocks in the Netherlands and Ireland, but the duration of the effect is shorter. Real uncertainty shocks do not appear to have a strong impact on GDP. In only two countries, the UK, and the Netherlands there is a negative and statistically significant response, and the negative effect does not immediately occur but after almost a year. The duration of the negative effect is also short, of less than two quarters.

Figure 2. Gross Domestic Product Response to Uncertainty Shocks (Baseline Model).

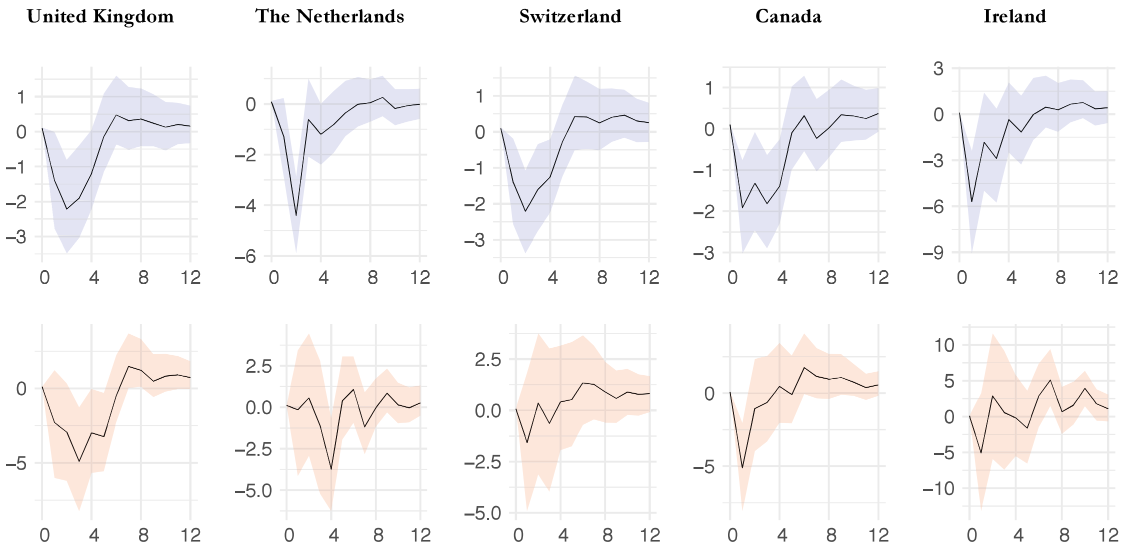

Fig 2. Gross Domestic Product Response to Uncertainty Shocks in the baseline model. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

The response of the stock market to financial shocks is negative, immediate and lasts between three and four quarters in all the countries. Interestingly, while mean reversion takes place about a year after the shock, our results do not show evidence of stock market over reaction. In other words, we do not observe a significant positive effect on the stock market in the medium term. Initial stock market losses are not automatically compensated by later gains derived from market over reaction during the recovery. The response of stock market to real uncertainty shocks is less clear. There are only statistically significant responses for very short periods of time in the UK, Switzerland, and Ireland. These responses, which are not immediate but rather occur after about three quarters, interestingly are different for the first country than for the other two. While in Switzerland and Ireland the response is negative, as expected, in the UK the response is positive. This result may indicate that when a real sector shock occurs in the US, the UK can benefit temporarily by improving its export position in global good markets. However, this positive effect last for just one quarter.

Figure 3. Stock Market Response to Uncertainty Shocks (Baseline Model).

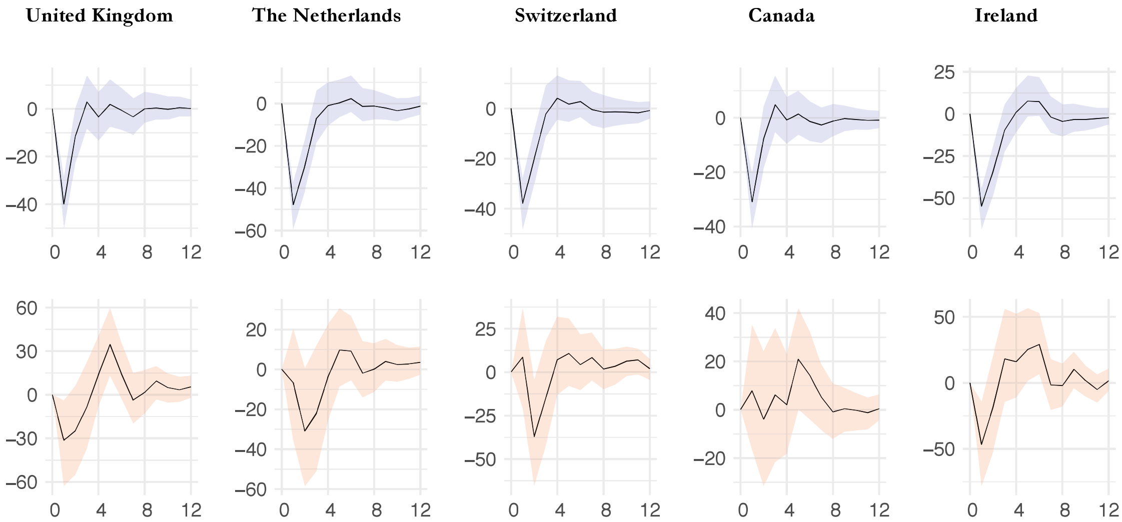

Fig 3. Stock Market Response to Uncertainty Shocks in the baseline model. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

The responses of interest rates and prices to uncertainty shocks are lower (see figures 4 and 5) than those shown above for the credit market, GDP, and the stock market. Results for the first model highlight three interesting findings: i). Financial uncertainty matters more for real and financial variables than real uncertainty; and ii). Financial variables are hit stronger by uncertainty shocks than real variables. These results are consistent with predictions of theoretical models posting that financial markets are vital for the macroeconomy because they provide the financing required for the development of investment plans. In that same line, shocks originating in financial markets affect firm financing conditions more strongly than shocks originating in the real sector and are potentially more harmful for the economy. Strong financial shocks lead to credit and capital market crunches that mostly affect small- and medium-sized enterprises (SMEs). These firms employ more than half of the private sector labor force in the five countries considered in this study. When bank lending is reduced, SMEs tend to be more vulnerable and affected than larger corporations (OECD, 2012) and credit sources tend to dry up more rapidly for small firms than for large companies during economic downturns (ECB, 2013). The reduction observed in GDP is then mainly derived from the difficulties encountered by many firms to obtain the funding required to maintain their previous production levels rather than by a rational response of producers to the occurrence of a real shock.

Figure 4. Interest Rate (yield) Response to Uncertainty Shocks (Baseline Model).

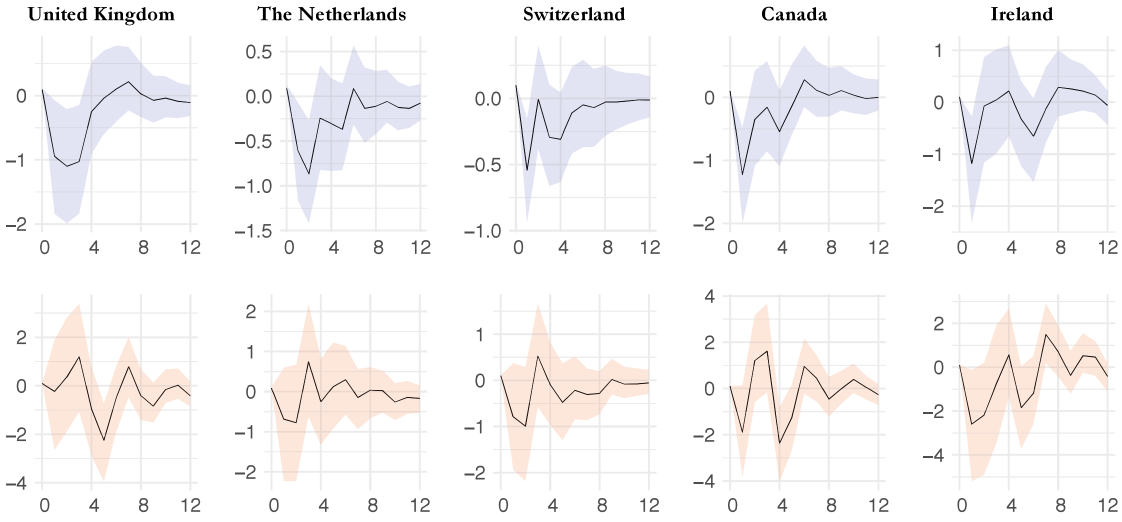

Fig 4. Interest Rate (yield) Response to Uncertainty Shocks in the baseline model. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 5. Price Response to Uncertainty Shocks (Baseline Model)

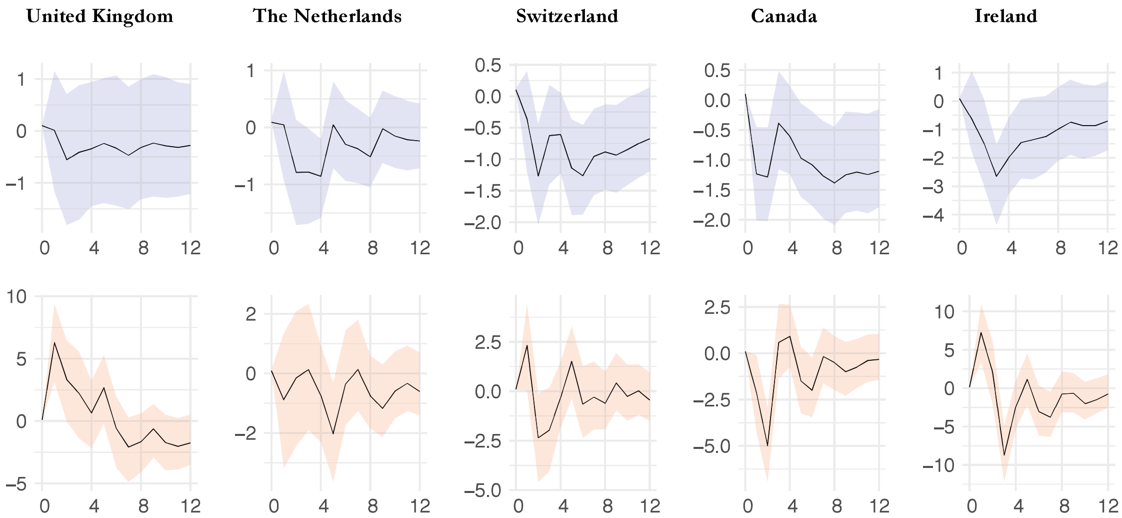

Fig 5. Price Response to Uncertainty Shocks in the baseline model. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs.

The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Table A1 in the Appendix presents one year ahead forecast error variance decomposition for each country. Variance decompositions indicate the amount of information each variable contributes to the other variables in the vector autoregression. They determine how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables. Uncertainty shocks play the main role in explaining the forecast error variance of each of the five macroeconomic and financial variables included in this study. More than 60 percent of each variable's one year ahead forecast error variance is explained by uncertainty shocks, and for credit, GDP, and stock prices this percentage is over 90 percent.

b) Model with non-orthogonal factors (original factors)

While in the baseline model above global factors were imposed to be orthogonal, in this subsection results are presented for the model with two non-orthogonal (original) factors. Results are qualitatively very similar to those shown above. Figures 6 to 10 depict impulse response functions for the five macroeconomic and financial variables considered in this study. Specifically, note that credit, GDP, and stock markets respond more strongly to financial shocks than to real shocks. Responses are not only larger in magnitude but are also longer in duration. These three variables react negatively to the occurrence of shocks, indicating that uncertainty affects the macroeconomy negatively.

These results are interesting, because they show that even when the two types of shocks are admitted being correlated, results are like those obtained when shocks are uncorrelated by construction (a stronger assumption). One year ahead forecast variance error decomposition results, shown in Table A2, are also quite like those shown in Table A1. Specifically, uncertainty variables are the most important in explaining the forecast variance error of all variables, including themselves.

Figure 6. Credit Response to Uncertainty Shocks (Model with Non-orthogonal Factors).

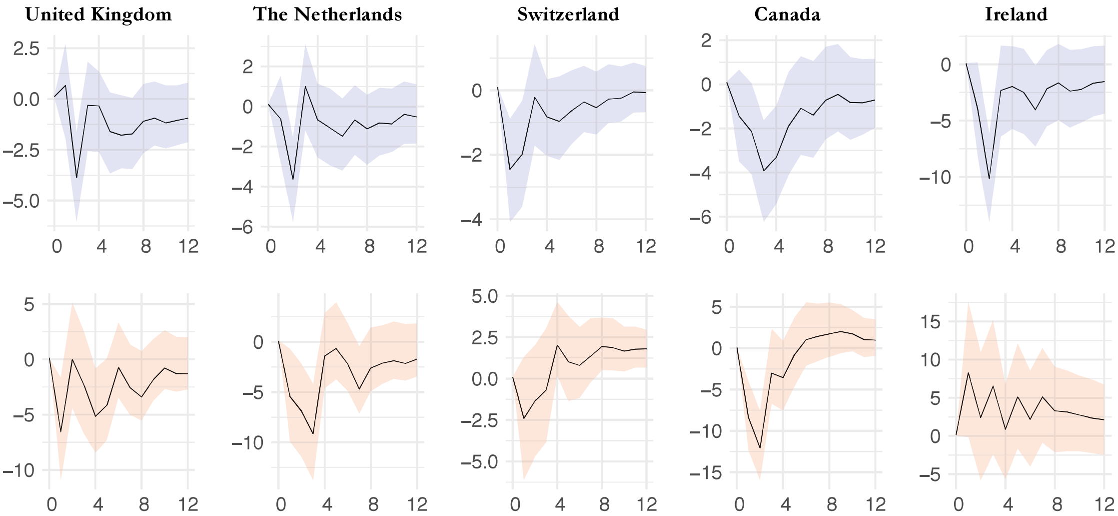

Fig 6. Credit Response to Uncertainty Shocks in the model with non-orthogonal factors. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 7. Gross Domestic Product Response to Uncertainty Shocks (Model with Non-orthogonal Factors).

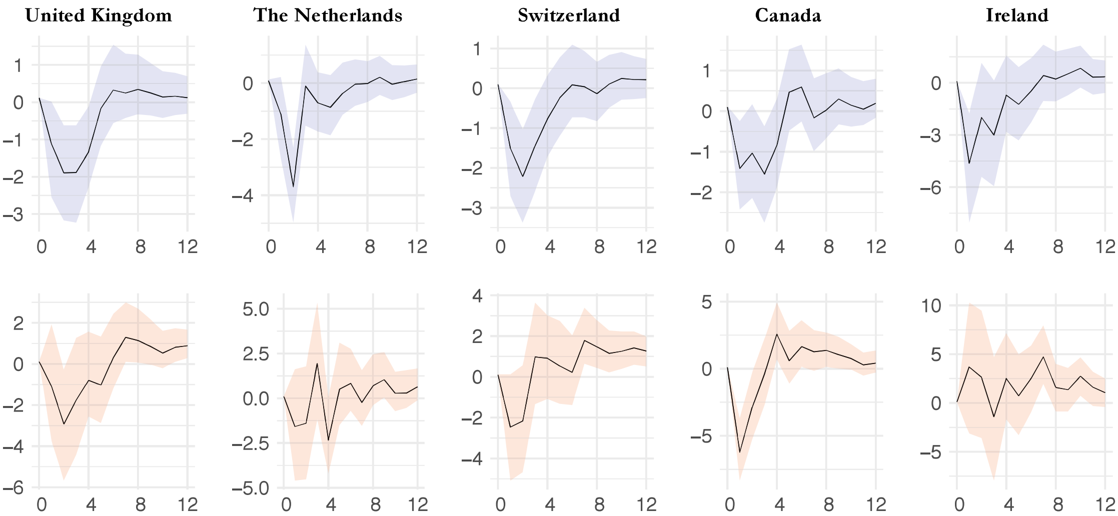

Figure 8. Stock Market Response to Uncertainty Shocks (Model with Non-orthogonal Factors).

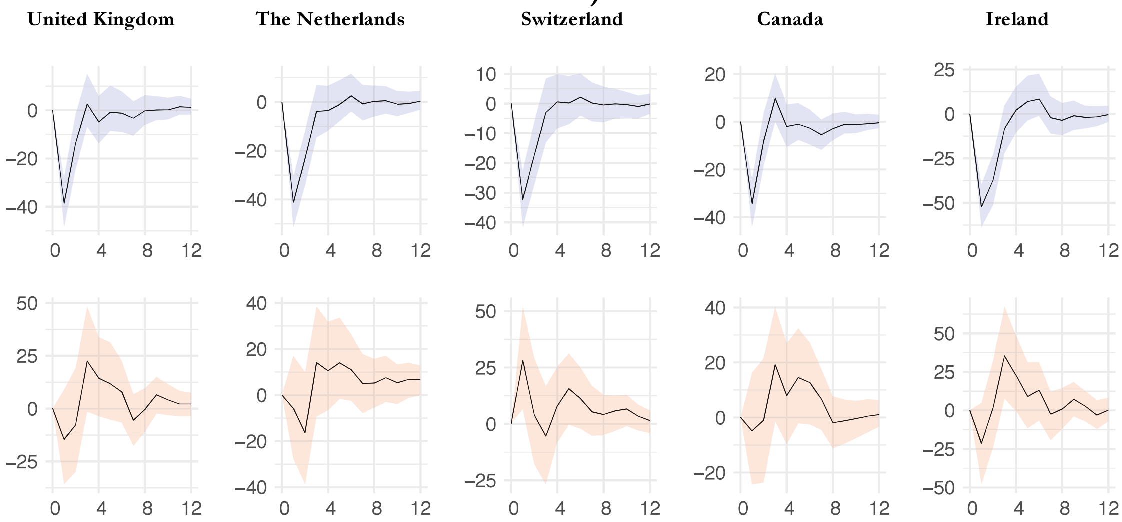

Fig 8. Stock Market Response to Uncertainty Shocks in the model with non-orthogonal factors. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 9. Interest Rate (yield) Response to Uncertainty Shocks (Model with Non-orthogonal Factors).

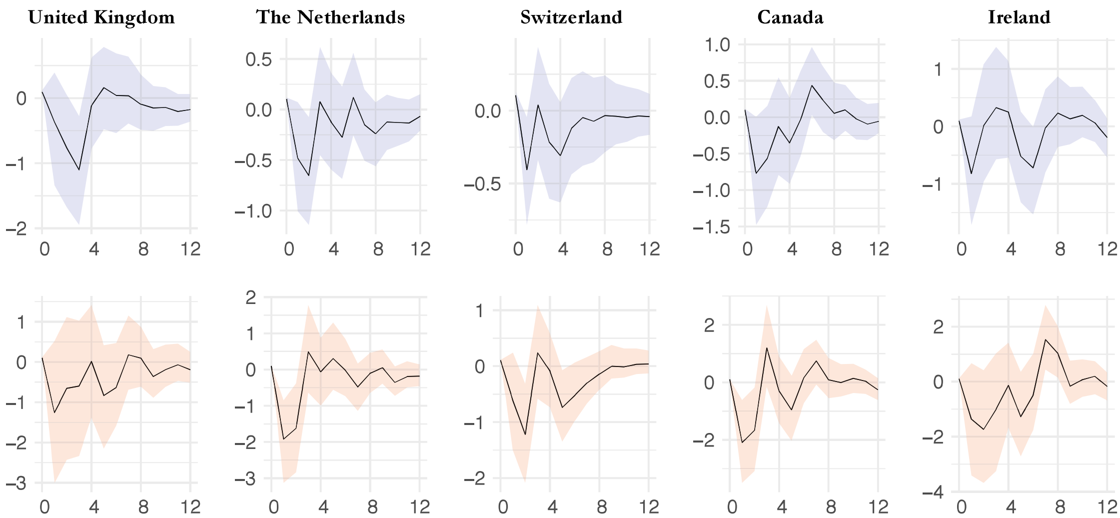

Fig 9. Interest Rate (yield) Response to Uncertainty Shocks in the model with non-orthogonal factors. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 10. Price Response to Uncertainty Shocks (Model with Non-orthogonal Factors).

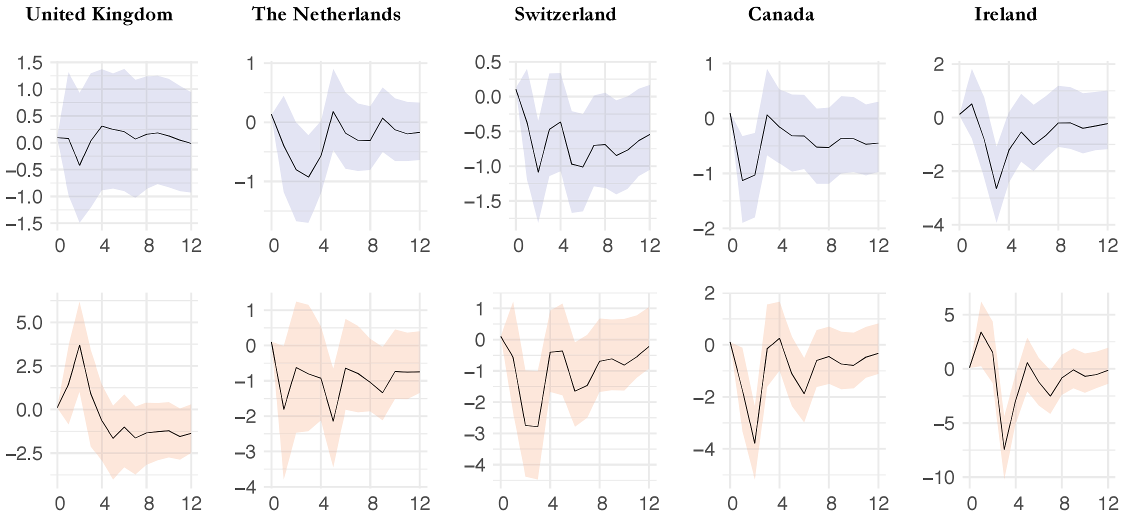

Fig 10. Price Response to Uncertainty Shocks in the model with non-orthogonal factors. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

c) Models using "keywords counting" for measuring financial distress and economic policy uncertainty

When "keyword counting" indexes of financial and economic policy uncertainty are used, results change considerably. As shown in the top panel of Figure 11, the effect of financial uncertainty measured this way on credit markets is unclear. For instance, impulse response functions show that the initial effect of a financial uncertainty shock is the reduction of credit in the economy. However, this effect last only two quarters and is followed by an increase in credit that also lasts two quarters. Then, mean reversion occurs and the effect disappears after one year. In Switzerland and Canada there is no statistically significant effect. In Ireland, a mild negative effect exists but is short-lasting. Finally, the Netherland presents a longer negative effect. Results for this country are like those obtained under the two specifications reported above.

Results obtained for the policy shock on credit are initially positive and statistically significant, surprisingly. Positive effects of policy uncertainty shocks are also reported for GDP and for the stock markets of some of the countries included in this study. These striking results may highlight an important limitation of "keyword counting" indexes as proxies for financial and policy uncertainty. They are based on word counting and, therefore, they cover both positive and negative events occurring in financial markets and the real economy. Therefore, they do not properly account for uncertainty in the sense that moments of higher uncertainty are associated with bad moments in which investors and bankers are more afraid of undertaking investment and financing decisions due to the opaqueness of possible future outcomes.

Figure 12 shows that financial uncertainty shocks initially generate a negative response in GDP in all countries, but after two or three quarters the effect changes and exhibits large time variability. Meanwhile, these shocks have no significant effects on stock markets, as observed in Figure 13.

Figure 11. Credit Response to Uncertainty Shocks (Model with "Keywords Counting").

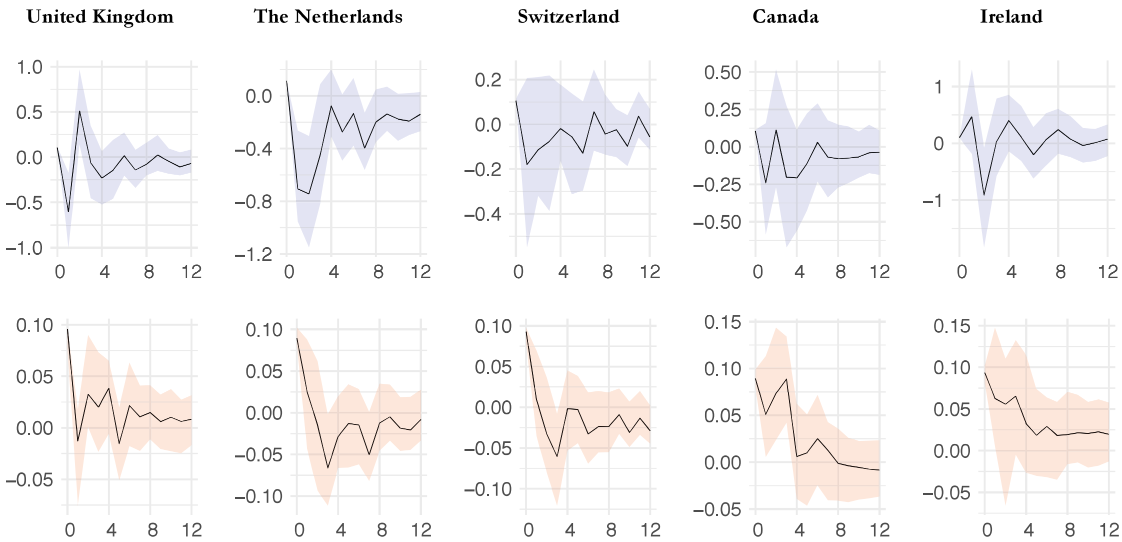

Fig 11. Credit Response to Uncertainty Shocks in the model using "keywords counting". **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to policy. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 12. Gross Domestic Product Response to Uncertainty Shocks (Model with "Keywords Counting").

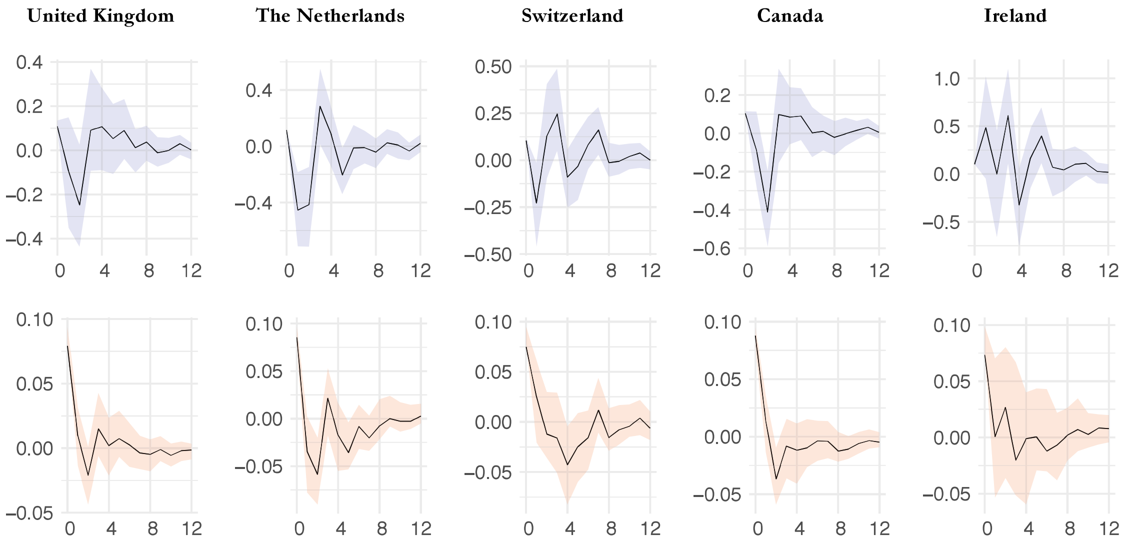

Fig 12. Gross Domestic Product Response to Uncertainty Shocks in the model using "keywords counting". **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to policy uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 13. Stock Market Response to Uncertainty Shocks (Model with "Keywords Counting").

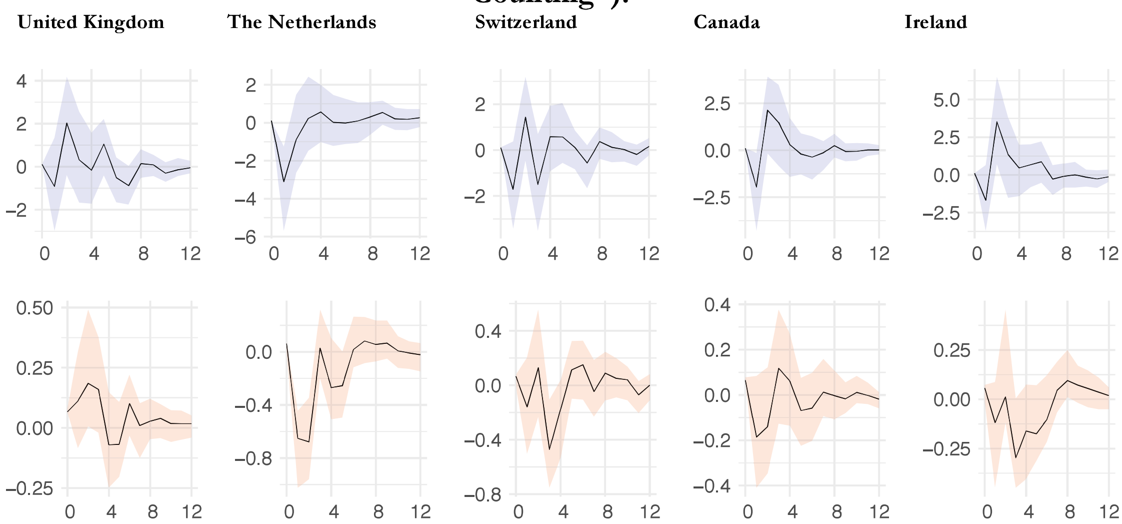

Fig 13. Stock Market Response to Uncertainty Shocks in the model using "keywords counting". **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to policy uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Interestingly, financial and policy uncertainty shocks constructed using "keyword counting" methods tend to increase interest rates for about two quarters and are also inflationary. The result of these shocks affects more clearly interest rates and prices than credit, GDP, and stock markets. This is probably a result of the way in which these indexes are constructed, relying heavily on news and innovations originating in monetary markets and in monetary policy.

Forecast variance error decomposition results in Table A3 are quite different from those seen in tables A1 and A2. Importantly, both uncertainty indexes lose importance in explaining the behavior of the forecast error variance of most included variables. This result further shows that uncertainty measures base on "keyword counting" probably account for a different concept of uncertainty than those constructed based on macroeconomic and financial market variables.

Figure 14. Interest Rate (yield) Response to Uncertainty Shocks (Model with "Keywords Counting").

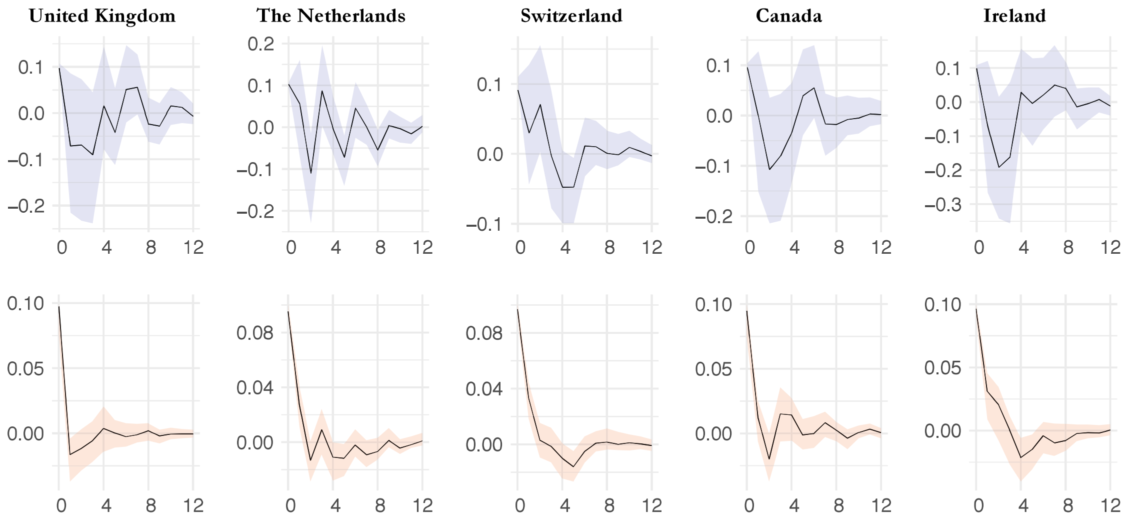

Fig 14. Interest Rate (yield) Response to Uncertainty Shocks in the model using "keywords counting". **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to policy uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 15. Price Response to Uncertainty Shocks (Model with "Keywords Counting").

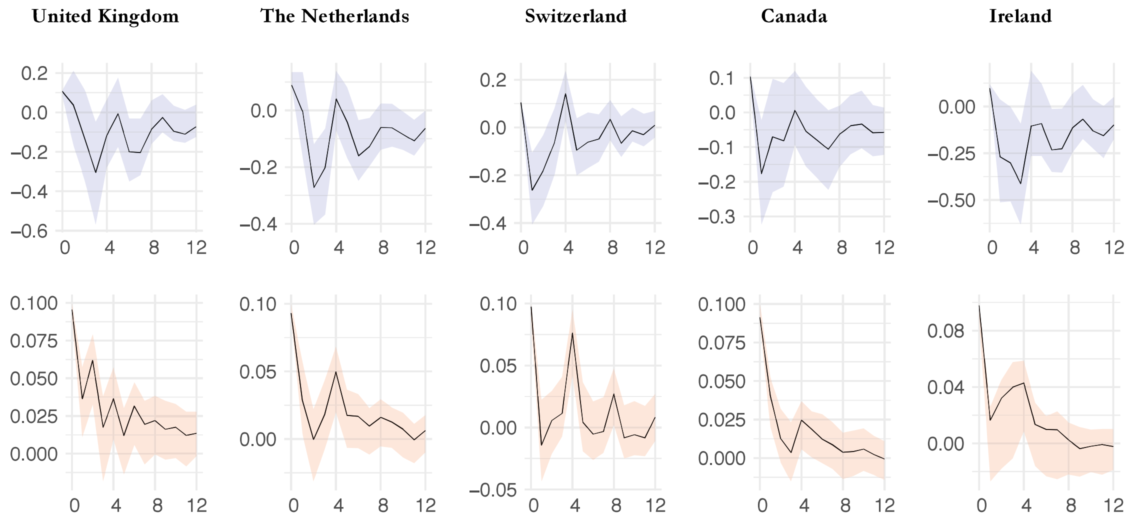

Fig 15. Price Response to Uncertainty Shocks in the model using "keywords counting". **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to policy uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

d) Model with US Fed Funds interest rate

Various studies approximate uncertainty shocks using the US Fed funds interest rate. The main idea is that the stance of the US monetary policy, which is exogenous to other countries in the world, is an important source of aggregate uncertainty. Hence, the effect of financial and real uncertainty indexes may be contaminated with the effect of US monetary policy shocks which can be controlled using the US Fed Funds interest rate. As a robustness check of our results, we estimate a FAVAR model in which this interest rate is included. Concretely, we estimate a model with one orthogonal global factor, the federal funds (shadow) rate, and our baseline financial and real uncertainty indexes. Figures 16 to 20 show the corresponding impulse response functions for the five macroeconomic and financial variables considered in this study.

Figure 16 shows responses of credit to financial uncertainty shocks (top panel) and Fed Funds interest rate shocks (bottom panel). Note that financial uncertainty shocks produce a negative response of at least two quarters in each of the five countries considered here. The response is stronger and longer for Canada, in which mean reversion takes more than four quarters to occur. The effect of the Fed Funds interest rate on credit is not as clear but seems to be positive initially for credit markets outside the US. This result may indicate that when monetary policy tightens in the US, credit markets in other developed economies find interesting lending opportunities to firms for which credit is more costly in the US and have access to other developed credit markets. Then, the tightening of financial conditions in the US, proxied by increases in the Fed Funds interest rate, lead to higher credit in these five developed countries. The effect lasts for about three quarters in most countries in which the effect is statistically significant.

These results indicate that the stance of the US monetary policy is not an ideal indicator of financial uncertainty. Therefore, studies using it as a measure of financial uncertainty may probably lead to mistaken results and conclusions of the effect of financial "uncertainty" on credit markets.

Similarly, Figure 17 shows that results on GDP are quite distinct for a financial uncertainty shock and a Fed Funds interest rate shock. While the former lead to output reduction of between two to four quarters in all five countries, the later takes to output increases initially, especially in Switzerland. This result indicates that the tightening of the US monetary policy leads to higher credit activity and higher economic activity in other developed countries like those included in this study.

Figure 16. Credit Response to Uncertainty Shocks (Model with US Fed Funds interest rate).

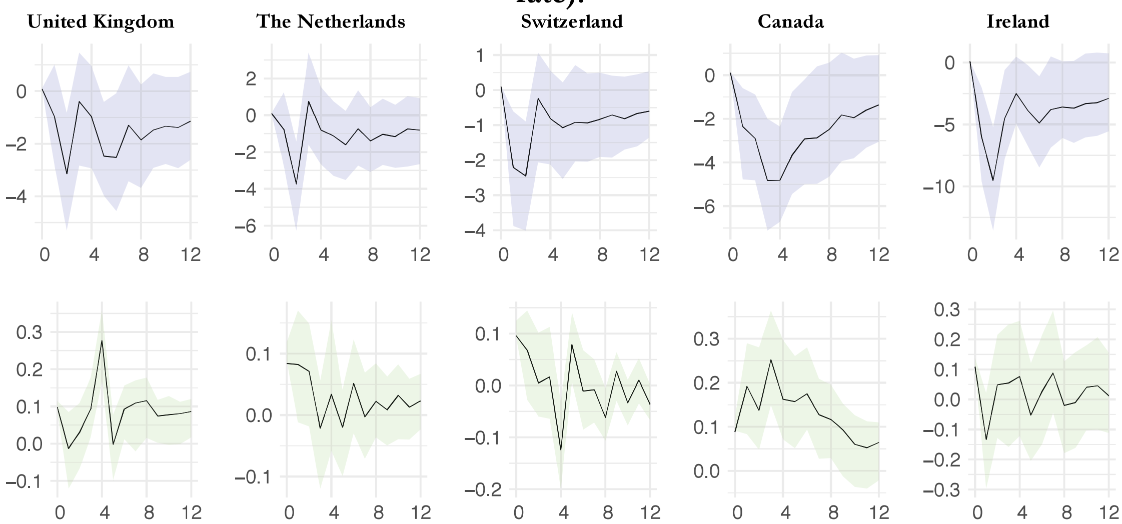

Fig 16. Credit Response to Uncertainty Shocks in the model with US Fed Funds interest rate. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to the federal funds rate. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Results shown in Figure 18 show that financial uncertainty shocks have negative impact on stock markets. Importantly, these effects are almost quantitatively identical to those reported in the baseline model. Hence, even when the Fed Funds interest rate is included in the FAVAR model, the measured effect of financial uncertainty on stock markets is negative and lasts for about a year in all countries. The effect of Fed Funds interest rate shocks on stock markets is initially negative, but the rebounds and generates a positive but short effect.

Figure 17. Gross Domestic Product Response to Uncertainty Shocks (Model with US Fed Funds interest rate).

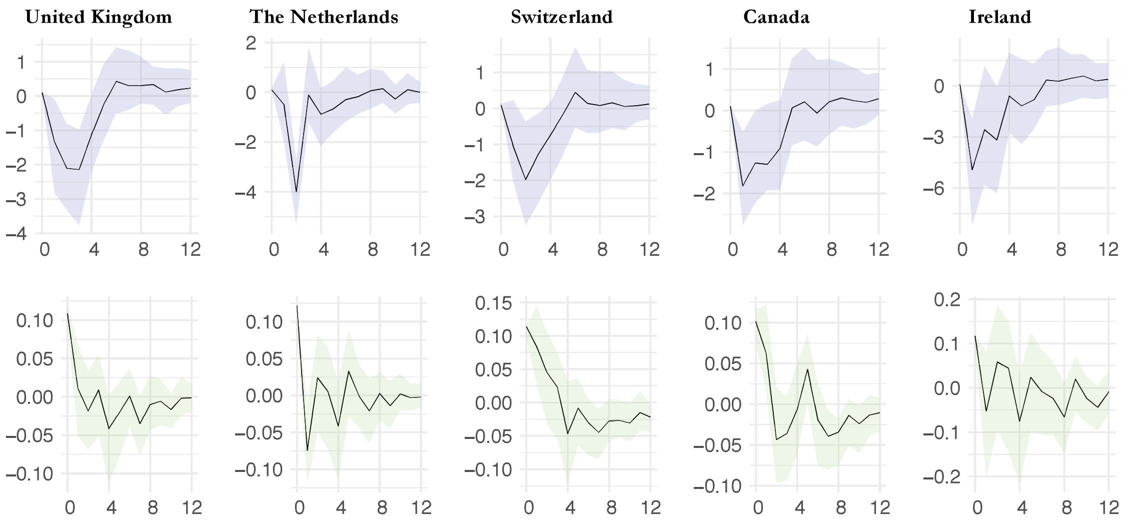

Fig 17. Gross Domestic Product Response to Uncertainty Shocks in the model with US Fed Funds interest rate. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to the federal funds rate. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 18. Stock Market Response to Uncertainty Shocks (Model with US Fed Funds interest rate).

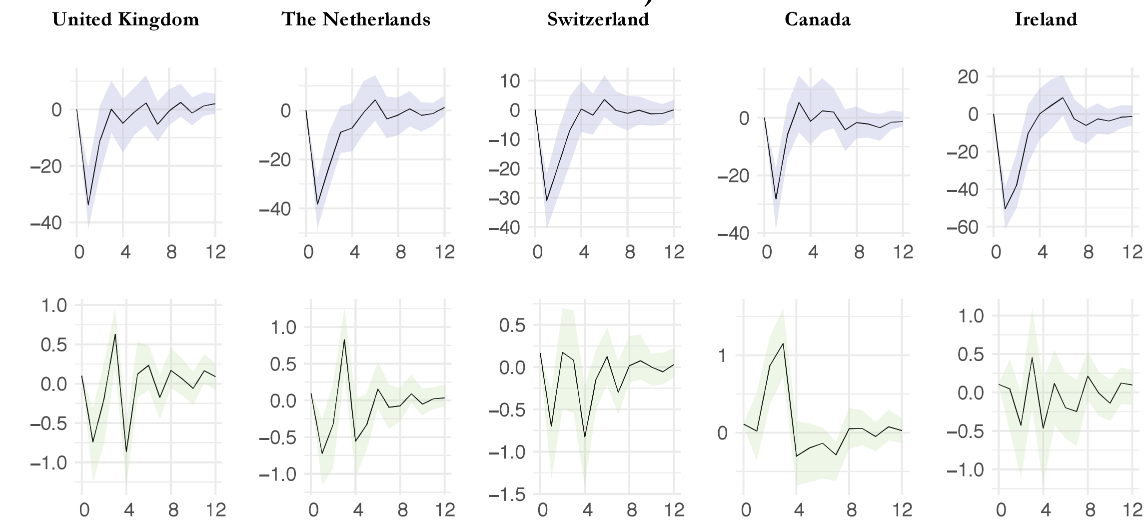

Fig 18. Stock Market Response to Uncertainty Shocks in the model with US Fed Funds interest rate. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to the federal funds rate. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Results of forecast error variance decomposition, which are not shown here, indicate that financial uncertainty contributed the most to the forecast error variance of all other variables included in the FAVAR model, including the Fed Funds interest rate. Hence, there is evidence that monetary policy responds to financial uncertainty shocks.

e) Model with sign restrictions

For additional robustness checks, the baseline model was estimated but the identification was achieved by sign restrictions where the stock markets and credit markets were assumed to decrease for one period after the occurrence of an uncertainty shock. Results under these restrictions are qualitatively identical. However, some quantitative differences are worthy of being mention. Particularly, the response of credit to financial uncertainty shocks is more prolonged than under the baseline model. For instance, the negative effect on Ireland's credit market does not disappear even 16 quarters after the occurrence of the shock. In Canada, the effects of the shock on the credit market disappear only eight quarters ahead (see Figure 19, top panel). Interestingly, similar results are obtained when a real uncertainty shock takes place.

Its effects on credit are more permanent than under the baseline model (see Figure 19, bottom panel).

The response of GDP to both financial and real uncertainty shocks are very similar to those obtained for the baseline model. A negative response, shorter in length than the response of credit, can be seen in Figure 20. However, the response is more immediate under this setting. Stock markets also respond negatively to uncertainty shocks. As in the case of credit and GDP, the response of stock markets to uncertainty shocks is longer under this model specification than under the baseline model, as shown in Figure 21.

Figure 19. Credit Response to Uncertainty Shocks (Model with sign restrictions).

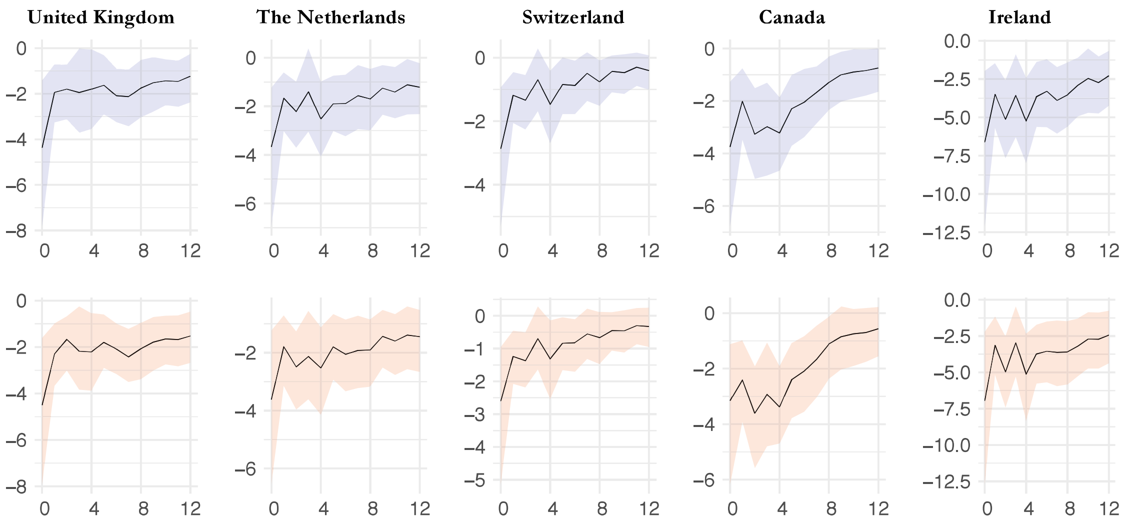

Fig 19. Credit Response to Uncertainty Shocks in the model with sign restrictions. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are credible intervals estimated by rotating the B matrix that reflect model uncertainty (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 20. Gross Domestic Product Response to Uncertainty Shocks (Model with sign restrictions).

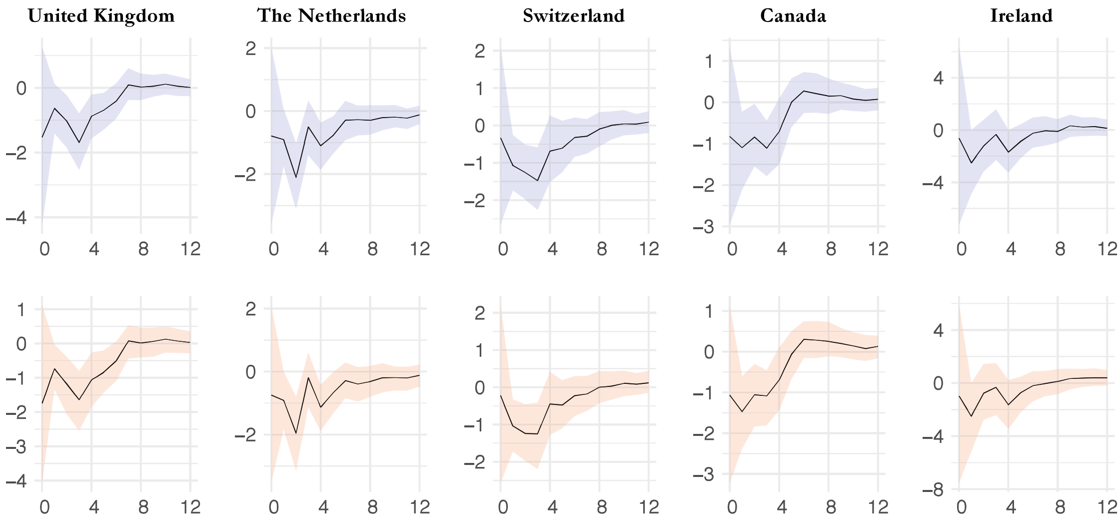

Fig 20. Gross Domestic Product Response to Uncertainty Shocks in the model with sign restrictions. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are credible intervals estimated by rotating the B matrix that reflect model uncertainty (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Figure 21. Stock Market Response to Uncertainty Shocks (Model with sign restrictions).

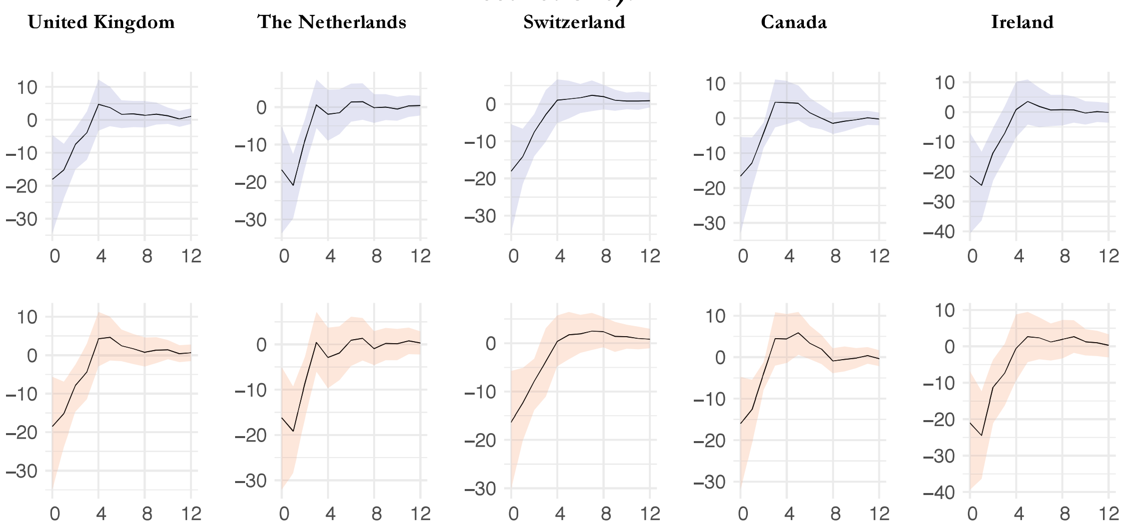

Fig 21. Stock Market Response to Uncertainty Shocks in the model with sign restrictions. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are credible intervals estimated by rotating the B matrix that reflect model uncertainty (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

f. Other countries

Finally, the baseline specification of the FAVAR model was estimated using five different developed countries, to test whether the main results presented above were specific to the initial set of countries or can be extended to developed countries more generally. Five developed countries in which US direct investment is not as important as in the first set of countries were selected: Germany, Italy, Sweden, Japan, and Australia. Figure 22 presents the response of credit to financial and real uncertainty shocks. Results are basically the same than those reported above. Financial uncertainty shocks are the main drivers of changes in credit. Specifically, credit is reduced after a financial uncertainty shock for all countries, except Japan. However, the duration of the effect is lower. Real uncertainty shocks also negatively affect credit, but less than financial uncertainty shocks do.

Figure 22. Credit Response to Uncertainty Shocks (Baseline Model for five different developed countries).

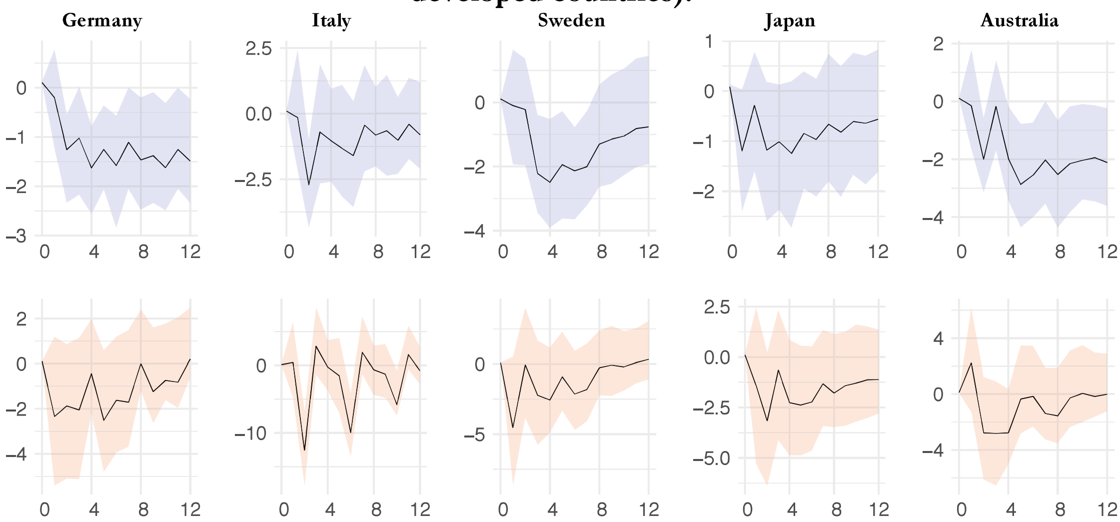

Fig 22. Credit Response to Uncertainty Shocks in the baseline model for five different developed countries. **Note:** (a) Top panel is a shock to financial uncertainty (b) Bottom panel is a shock to real uncertainty. The black line is the median of the identified IRFs. The horizontal axis is time, measured in quarters. The shadowed areas are confidence intervals estimated by bootstrapping (16th and 84th percentiles). The estimation period is 1963q4 – 2019q4.

Interestingly, the effect of financial uncertainty shocks on GDP is negative and of stronger magnitude and larger duration than for the first set of countries. Real uncertainty shocks affect GDP only in Germany, in which GDP reduces for three quarters, and in Japan. Finally, the response of stock markets to financial and real uncertainty shocks is practically identical than for the first set of five countries. Stock markets basically negatively respond to financial uncertainty shocks, with a duration of about four quarters.

Summing-up, results are consistent and robust under all the specifications presented above. Uncertainty shocks are important drivers of changes in real and financial markets. However, financial shocks appear to matter more, especially for credit, GDP, and stock markets. Financial markets react first to uncertainty shocks than real variables do. Additionally, effects are longer in financial markets. Results when using uncertainty measures based upon "keyword counting" are very different than those obtained when traditional uncertainty indexes are used. Results under these "keyword counting" indexes are counter intuitive. Finally, the importance of uncertainty indexes as the main drivers of shocks to financial markets and to the real economy remains unchanged even when the Fed Funds interest rate is included in the FAVAR model.

6. Conclusions

This paper studies the propagation of uncertainty shocks to the economy, studying their impact on real and financial variables. We use currently developed measures of financial, real, and policy uncertainty in the US and study their impact on ten developed economies. The main contributions to the literature are four. First, using various specifications of the model, we show that financial uncertainty matters most as a shock transmission mechanism to the economy. While real uncertainty shocks affect real and financial variables in some countries, the effect is lagged and short-lasting. On the contrary, financial uncertainty shocks affect these variables for long periods of time in most countries (between one semester and one year, depending on the country and on the model specification).

Second, unlike most papers in the literature we study the transmission channels through which uncertainty propagates into the economy. We show that uncertainty shocks affect financial markets immediately and then affect GDP with a lag. This result is coherent with postulates of "old" Keynesian macroeconomics in which credit and financial market conditions are important for macroeconomic outcomes.

Third, by studying the effect of US uncertainty measures on several developed countries, our model captures the global nature of uncertainty that must be included in economic modeling for identification purposes. Uncertainty measures are truly exogenous to the other variables in our setting. Additionally, uncertainty, credit, output, and prices are driven by global factors, and the joint modeling of these phenomena requires going beyond the traditional focus on individual countries that characterize the previous macro-uncertainty literature. Finally, our results highlight the importance of taking fundamental uncertainty seriously: It is the unexpected, unpredictable component of uncertainty measures that matter.

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Appendix

Table 1. Forecast Error Variance Decomposition for the Baseline Model (One Year Ahead)

United Kingdom

	Credit	GDP	Shares	Int.R.	prices
Credit	0.93	0.02	0.02	0.23	0.04
GDP	0.15	2.08	0.11	0.51	0.08
Shares	0.00	0.00	0.03	0.06	0.01
Int.R.	0.28	0.07	0.04	17.88	0.15
prices	0.11	0.07	0.00	0.34	2.07
F1	0.01	0.03	0.04	0.22	0.11
F2	0.02	0.02	0.00	0.13	0.05
Un.Fin	16.09	21.16	50.90	53.29	0.85
Un.Real	82.40	76.55	48.86	27.35	96.64

The Netherlands

	Credit	GDP	Shares	Int.R.	prices
Credit	0.77	0.02	0.01	0.34	0.73
GDP	0.09	4.36	0.04	0.30	0.62
Shares	0.01	0.01	0.03	0.15	0.23
Int.R.	0.86	0.74	0.63	27.57	0.93
prices	0.05	0.35	0.17	0.33	32.58
F1	0.01	0.04	0.02	0.52	0.38
F2	0.01	0.08	0.00	0.34	0.29
Un.Fin	11.66	88.02	67.69	29.59	38.53
Un.Real	86.53	6.39	31.40	40.86	25.73

Switzlerland

	Credit	GDP	Shares	Int.R.	prices
Credit	3.10	0.28	0.00	0.40	0.11
GDP	0.23	7.41	0.00	0.42	0.08
Shares	0.01	0.00	0.03	0.14	0.05
Int.R.	1.46	1.29	0.84	33.39	0.44
prices	0.03	0.13	0.24	0.13	5.62
F1	0.05	0.15	0.03	0.35	0.12
F2	0.04	0.15	0.02	0.34	0.05
Un.Fin	42.41	68.55	51.83	11.11	11.81
Un.Real	52.68	22.02	47.00	53.71	81.73

Canada

	Credit	GDP	Shares	Int.R.	prices
Credit	0.68	0.01	0.02	0.14	0.07
GDP	0.32	2.76	0.03	0.23	0.05
Shares	0.01	0.00	0.09	0.05	0.02
Int.R.	0.13	0.27	0.49	9.76	0.21
prices	0.15	0.11	0.12	0.36	3.08
F1	0.06	0.04	0.02	0.16	0.05
F2	0.02	0.05	0.04	0.13	0.02
Un.Fin	16.82	23.15	89.28	15.93	9.74
Un.Real	81.81	73.61	9.91	73.24	86.76

Ireland

	Credit	GDP	Shares	Int.R.	prices
Credit	0.80	0.04	0.00	0.09	0.01
GDP	0.06	1.37	0.00	0.06	0.01
Shares	0.01	0.00	0.01	0.02	0.00
Int.R.	0.41	0.03	0.13	7.67	0.12
prices	0.10	0.01	0.06	0.33	0.77
F1	0.03	0.09	0.02	0.08	0.03
F2	0.03	0.03	0.01	0.12	0.03
Un.Fin	88.19	55.32	59.94	9.57	6.68
Un.Real	10.38	43.10	39.83	82.05	92.35

Table 2. Forecast Error Variance Decomposition for the Model with Non-orthogonal Factors (One Year Ahead)

United Kingdom

	Credit	GDP	Shares	Int.R.	prices
Credit	1.60	0.05	0.03	0.37	0.09
GDP	0.32	4.61	0.13	0.42	0.28
Shares	0.00	0.01	0.04	0.09	0.04
Int.R.	0.52	0.16	0.07	19.30	0.47
prices	0.42	0.18	0.00	0.39	6.20
F1	0.03	0.08	0.05	0.25	0.42
F2	0.03	0.04	0.00	0.20	0.06
Un.Fin	23.65	37.66	68.14	35.50	1.06
Un.Real	73.44	57.22	31.54	43.50	91.38

The Netherlands

	Credit	GDP	Shares	Int.R.	prices
Credit	0.58	0.02	0.02	0.18	0.17
GDP	0.07	4.36	0.06	0.17	0.42
Shares	0.01	0.01	0.05	0.06	0.08
Int.R.	0.67	0.68	1.10	13.08	0.40
prices	0.04	0.19	0.37	0.19	14.45
F1	0.01	0.08	0.03	0.14	0.20
F2	0.01	0.10	0.00	0.12	0.13
Un.Fin	8.31	61.05	80.51	8.01	23.61
Un.Real	90.30	33.52	17.85	78.04	60.55

Switzlerland

	Credit	GDP	Shares	Int.R.	prices
Credit	5.25	0.23	0.01	0.44	0.10
GDP	0.36	4.55	0.00	0.29	0.08
Shares	0.02	0.01	0.05	0.29	0.02
Int.R.	2.35	0.76	1.39	34.52	0.41
prices	0.11	0.12	0.42	0.42	5.56
F1	0.06	0.10	0.06	0.18	0.11
F2	0.07	0.10	0.03	0.38	0.06
Un.Fin	50.87	41.65	60.41	6.60	8.48
Un.Real	40.90	52.49	37.63	56.88	85.18

Canada

	Credit	GDP	Shares	Int.R.	prices
Credit	0.49	0.01	0.00	0.12	0.08
GDP	0.20	1.91	0.02	0.18	0.09
Shares	0.00	0.00	0.06	0.05	0.03
Int.R.	0.06	0.22	0.24	9.60	0.22
prices	0.02	0.14	0.09	0.25	5.00
F1	0.06	0.03	0.02	0.17	0.08
F2	0.00	0.03	0.03	0.13	0.05
Un.Fin	8.87	10.17	76.83	8.80	11.24
Un.Real	90.31	87.48	22.71	80.70	83.19

Ireland

	Credit	GDP	Shares	Int.R.	prices
Credit	0.52	0.06	0.00	0.18	0.03
GDP	0.04	1.87	0.00	0.10	0.03
Shares	0.00	0.00	0.02	0.04	0.01
Int.R.	0.18	0.06	0.16	14.34	0.21
prices	0.06	0.02	0.05	0.45	1.36
F1	0.02	0.13	0.03	0.14	0.07
F2	0.02	0.04	0.01	0.18	0.03
Un.Fin	51.00	59.01	70.92	9.96	10.03
Un.Real	48.15	38.80	28.82	74.61	88.24

Table 3. Forecast Error Variance Decomposition for the Model with "Keywords Counting" (One Year Ahead)

United Kingdom

	Credit	GDP	Shares	Int.R.	prices
Credit	43.96	1.05	3.75	0.81	0.66
GDP	7.98	80.85	22.60	1.54	4.00
Shares	0.14	0.19	8.93	0.60	1.08
Int.R.	8.69	4.41	3.88	89.93	7.54
prices	10.40	2.49	0.86	1.55	72.65
F1	0.94	1.66	12.61	1.35	4.53
F2	1.18	1.71	3.04	0.99	1.23
FSI	26.26	7.08	43.67	2.36	7.43
EPU	0.44	0.56	0.66	0.85	0.88

The Netherlands

	Credit	GDP	Shares	Int.R.	prices
Credit	30.51	0.58	2.05	1.39	1.23
GDP	2.36	54.88	3.17	1.06	2.39
Shares	0.77	0.30	3.03	0.92	1.11
Int.R.	24.90	15.82	59.64	89.10	2.49
prices	1.98	2.01	14.13	1.29	79.95
F1	0.44	0.63	1.68	1.36	1.54
F2	1.20	0.90	0.11	1.43	1.05
FSI	37.44	24.24	14.92	2.64	9.48
EPU	0.39	0.64	1.27	0.80	0.76

Switzlerland

	Credit	GDP	Shares	Int.R.	prices
Credit	59.66	3.66	0.62	1.05	1.39
GDP	4.35	70.84	0.30	0.92	1.11
Shares	0.31	0.09	2.67	1.10	0.91
Int.R.	28.29	10.28	57.18	91.76	4.00
prices	1.20	1.18	16.96	0.90	79.82
F1	0.59	1.81	3.94	1.05	1.30
F2	1.27	1.92	2.53	1.21	1.52
FSI	3.57	9.76	15.23	1.15	9.17
EPU	0.77	0.47	0.56	0.85	0.77

Canada

	Credit	GDP	Shares	Int.R.	prices
Credit	50.74	0.45	0.34	0.98	1.59
GDP	25.33	72.92	1.93	1.34	2.14
Shares	0.63	0.11	4.21	1.11	1.11
Int.R.	5.31	6.98	34.26	88.64	3.88
prices	3.64	2.79	10.33	2.11	83.71
F1	6.88	1.41	1.56	1.18	1.49
F2	1.39	1.07	3.25	1.47	0.91
FSI	5.08	13.62	43.84	2.33	4.34
EPU	0.98	0.64	0.30	0.84	0.82

Ireland

	Credit	GDP	Shares	Int.R.	prices
Credit	39.88	1.64	0.07	0.79	0.82
GDP	2.85	57.75	0.19	1.02	1.79
Shares	0.56	0.14	3.53	1.02	1.06
Int.R.	12.96	1.05	31.90	84.73	8.52
prices	2.95	1.80	4.89	2.50	62.26
F1	2.02	2.95	5.62	1.40	3.74
F2	2.28	1.13	0.97	1.84	1.34
FSI	35.82	33.19	52.51	5.87	19.75
EPU	0.68	0.35	0.32	0.81	0.71

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